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Deep Neuro-Fuzzy Approach for Risk and Severity Prediction using Recommendation Systems in Connected Healthcare †

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Abstract

Internet of Things (IoT) and Data science has revolutionised the entire technological landscape across the globe. Due to this reason, the healthcare ecosystems are adopting the cutting edge technologies to provide assistive and personalised care to the patients. But, this vision is incomplete without the adoption of data-focused mechanisms (like machine learning, big data analytics) that can act as enablers to provide early detection and treatment of patients even without admission in the hospitals. Recently, there has been an increasing trend of providing assistive recommendation and timely alerts regarding the severity of the disease to the patients. Even, remote monitoring of the present day health situation of the patient is possible these days though the analysis of the data generated by IoT devices by doctors. Motivated from these facts, we design a healthcare recommendation system that provides a multi-level decision making related to the risk and severity of the patient diseases. The proposed systems use an all-disease classification mechanism based on convolutional neural networks to segregate different diseases on the basis of the vital parameters of a patient. After classification, a fuzzy inference system is used to compute the risk levels for the patients. In the last step, based on the information provided by the risk analysis, the patients are provided with the potential recommendation about the severity staging of the associated diseases for timely and suitable treatment. The proposed work has been evaluated using different datasets related to the diseases and the outcomes seem to be promising.

KEYWORDS:
Convolution Neural Networks; Type-2 Fuzzy System; Classification; Risk and Severity Prediction

1 | INTRODUCTION

In this digital world, people are more susceptible to copious medical issues due to their inactive lifestyle. The expenditures on medical treatments continue to expand and so everyone is inclined towards online service for the resolution of healthcare issues to save time and money. As more people are affected by a wide range of diseases, a lot of attention is being paid to provide suitable medication for these diseases. In recent times, the web has been a significant hot-spot for people to approach healthcare services. In the current COVID scenarios, the online healthcare systems have proved to of huge benefit when the patients cannot be treated physically. Because of such scenarios, the online health care systems are gaining wide attention from the research community also. There are many studies ongoing for exploring the ways to provide patient-driven platforms and

†NeuroFuzzClass.

system for medications, through the adoption of big data analytic and deep learning into healthcare practices. The resultant is reduced expenditure on irrelevant drugs and medical practices by having useful scrutiny on a large complex data that is generated by the healthcare systems [1]. According to a recent study, 81% of the grown-ups in the USA use Internet services and among them, 59% are worried only about diseases [2], disease analysis and different medicines. In the future, the patient is subject to turn into a functioning associate in the basic decision process of the healthcare systems [3]. This perspective is often known as patient strengthening. Medical and social economy are scruffier to one another and are beyond the realm of imagination to expect to accomplish the one without another. There is a different scope of medicinal services frameworks that are flexible programmed structures to determine the choices dependent on some substantial input information parameters.

As big data and learning technologies evolved, the recommender system has gained popularity in terms of providing online suggestive treatment to the patients. In COVID situation, a lot of countries (like NHS in the UK) are using recommendation systems to provide suggestions to the patients about the diseases and illness that can further project the need of any treatment or follow up from the doctor. This journey started in the early 90s when it was recognized that there is a requirement of information filtering techniques to fetch the patient information effectively. Recommender systems enable the diagnosis of patients to assist the physician as well as patients by using suggestive personal health advisory tools [4]. They are dependent on the software technologies and procedures that utilise the data related to all the medical verticals to create the suggestions consequently for the healthfulness of the patient. The generated suggestions aim to support the patients on various decisions related to further treatment and medications. The health recommender systems (HRS) are used as a diagnostic assistant by the consultants or doctors for providing personal health-related suggestions to the patients. HRS plays a significant role in self-diagnostics searches of patients over the web and given categories. It likewise helps for basic decision making regarding the customized patient care [5], to distinguishing key feeling pioneers among healthcare advisors [6], for supporting the patient to learn preventive measures, and health care tips [7,8]. Evermore, the current healthcare frameworks use the data provided by the patient to suggest the appropriate doctors for treatment. Thus, prescribing patients with specialist's doctor depends on their past discussion history that is utilized as a knowledge base for the design of an effective recommender framework. There are different kinds of recommendation frameworks prevalent across the world. A few of them are discussed below.

- *Two-dimensional recommender systems:* These systems provide suggestions to users without mulling over the conditions and other logical data proposals.
- *Context-aware recommender systems:* These systems [9] considers extra data other than clients, such as things and the evaluations that might be important at the current time to make a suggestion. They help to consolidate the usefulness of a computerized picture with a functioning recommender mode [10] by utilizing the data that is derived from the personal user and contextual data gathered by using sensors from the user's mobile phone.
- *Stage-based recommender systems:* These kinds of recommendation frameworks use the data accumulated by the sensors that are implanted in the surroundings. These model carefully identifies a suitable suggestion at a point of time. In this case, the contextual information is limited to the period, i.e., morning, forenoon, lunchtime, evening or night. Along with this, the weather conditions also affect the contextual information, i.e., good or bad weather conditions. In [11], an activity-awareness for human-engaged wellness applications and Knowledge Acquisition and Reasoning Engine were designed. These are stage-based recommender frameworks that demonstrate to incorporate a connection between fundamental medical primitives of clients.
- *Content-based recommender system:* These systems perform the decision making based on the historical data and recent priorities of the patients. The prediction relies on the features of the considered items.
- *Hybrid healthcare recommender system:* These systems are a combination of context-based and content-based information systems. These are measured as one of the most accurate systems.

The different recommender system models experience various challenges [12], like in different medicinal spaces prescription, the medications are yet juvenile regarding the dependability, reliability, and quality issues. From a patient's perspective, such frameworks are sufficiently skilled to give characterized, reliable and secure suggestion [3]. To overcome these issues, various methods are proposed, including the usage of machine/deep learning for the improvement of the overall recommendation process. Even, the deep learning is being seen as promising in numerous application fields, for example, personal computer vision, object acknowledgement, speech acknowledgement, regular natural language handling and robotic control where it demonstrates its capacity. Deep learning involves analyzing dimensions of data, relating to a chain of importance of highlights, components or ideas, where higher-level ideas are characterized from lower-level ones, and a similar lower level idea can characterize numerous higher level ideas. In recent time, Convolution Neural Networks (CNN) is a forwarder neural framework [13,5] that can be suitable to design the healthcare recommendation systems.

Recommender system is a subclass of information filtering that provides precise and personalized information for a specific field. In the current global scenario, if we correlate the situation with pandemics and national emergencies, recommender systems can prove its importance or play a crucial role in personalized services in the healthcare domain. A substantial amount of research has been done in the field of healthcare recommendation system, but still, it is one of the major topics of study. The majority of research has been conducted in domains such as hospitals management, health monitoring, tele-consultancy, record tracking and data management. Several issues are yet to be resolved in the healthcare domain such as lack of supportive infrastructure, high bandwidth specific tools and knowledge for usability. Moreover, the issues related to data loss, data corruption, data integrity, fear related to technology failure also affects the recommender system. To resolve the above issues, in this paper, the main contribution relates to the design of an intelligent recommender framework using a disease classification mechanism that predicts risk related to the diseases and thereafter uses a recommendation algorithm to analyze the medical data of patients. The CNN algorithm is employed for the disease classification process followed by a fuzzy inference system that takes the input from the classification process and calculates the risk level. Finally, the proposed recommendation system provides the suggestion to the patient according to the risk level predicted by the fuzzy system.

2 | RELATED WORK

The rise of recommender systems in the therapeutic field is credited to their practicality in predicting and recommending suitable outcomes to users. Subsequently, recommender systems deal with interminable malady, which also gives instructions to patients limiting both the danger of an ailment related with it. Accuracy is the fundamental feature of recommender systems they ought to limit false positive and false negative errors. The recent advancements have supported the adoption of artificial intelligence and machine learning methods for proficient expectations [14,15,16,17], which help therapeutic specialists in settling to a reasonable choice of treatment for various contaminations at a starting time. The methodology of ailment investigation depends strongly on hypochondriac and clinical test data. Information mining and machine learning calculations are used for disease estimation using the available information. The prediction models have been remarked to evaluate the measurement of various sicknesses using clinical test readings, rules, signs, and reactions. A recommended parameter of cholesterol, fasting blood sugar, blood pressure and oxygen saturation viably forecast the infection chance in different populace tests. The essential objective is to deal with big data containing unstructured information in a verified manner. Big data investigation includes a recommendation framework for forecast models which essentially concentrate after investigating huge data and anticipate a significant plan. The above idea can be associated with every single restorative assistance territory going from the expectation of infections to foreseeing physical activities to improve the well-being of patients. Social health insurance is moving from an illness centred model towards a patient-focused model.

Researchers have used an artificial intelligence-based supervised learning approach for the design of effective healthcare systems [18,19,20,21,22] to deal with chronic diseases. Zhang *et al.* [18] proposes an ensemble of three classifiers, i.e., artificial neural system, least squares support vector machine, and Naive Bayes to build a gathering structure. A real-time arrangement telehealth information gathered from coronary illness patients are applied for test evaluation. Artificial Neural Network is a supervised learning machine calculation that can be used to offer convincing responses for some intricate modelling issues. Least Square Support Vector Machine (LS-SVM) is a managed artificial intelligence method that depends on statistical learning hypothesis. The Naive Bayes classifier is a machine learning classifier that is based on the probability model with the possibility that the factors are autonomous from one another. The information succession of the sliding windows dependent on the sick person's time arrangement information is disintegrated through utilizing the fast Fourier transformation so as for removing recurrence data. The outcomes definitively determine, the planned framework is an auspicious apparatus for breaking down time arrangement restorative information besides giving exact suggestions to patient's suffering with the chronic heart ailments. In [19], the authors utilized the MKL technique along with ANFIS classifier to separate parameters between coronary illness patients and ordinary individuals. MKL strategy is utilized to scatter component factors among sound and patient (coronary illness) information with diminished measurements. ANFIS comprises of Sugeno fuzzy inference model (SFIM) with multi-layer Artificial Neural Network (ANN). The ANFIS structure utilizes versatile and non-adaptive nodes in different layers. The proposed methodology delivers high specificity rate value when contrasted with other existing deep learning method. Likewise, in [20], the authors suggest a recommender framework strategy on a mixture technique utilizing numerous classifications bound with the collaborative filtering. To improve the idea of therapeutic administrations, it's essential to use big data investigations in human services. Archenna *et al.*[23] provided knowledge on the most proficient method to utilize big information analytics to design a real health framework by examining variant organized human services information.

Unsupervised machine learning approaches are also helpful in providing healthcare services as suggested in various existing approaches[24,25,26]. In[24], the authors used a Bayesian non-negative matrix factorization procedure to design a pre-grouping count acclimated to the proposed probabilistic strategy. The results from a couple of open informational assortments seem definitive about clustering quality improvement when Bayesian non-negative matrix factorization is utilized, likened with the old-style matrix factorization or to the improved K-Means results and complex expectations precision utilizing framework factorization-based methods than utilizing improved K-Means. The authors in[25] presented CADRE, in which they bunched the medications into a few gatherings as per the utilitarian portrayal data and plan, based on crucial customized tranquillize based on clients or patients collaborative filtering. The insufficiency's of collaborative filtering methods relates to data sparsity, expensive, and cold start. The authors proposed a cloud-aided approach for inspiring end-user quality of experience of the drug system as a solution. The association rules speak to a promising method to improve coronary illness forecast. But, when association rule-based techniques are connected on a therapeutic informational index, they yield an incredibly enormous count of guidelines. The authors in[26] explain these restrictions and present calculations that utilize seek limitations to diminish the number of principles, looks for affiliation manages on a preparation set, lastly approves to an autonomous testing set. The medical health centrality of found principles is assessed with help, certainty, and lift. Affiliation rules are connected on a genuine informational index containing therapeutic records of patients with coronary illness. There is no major consideration on the accuracy, risk assessment and severity assessment in the context of unsupervised machine learning approaches.

In[27], a hybrid recommender framework, utilizing supervised and unsupervised is proposed to help the general practitioner in customized clinical medicine by incorporating ANN and CBR. In this framework, the data mined from content improves the understanding of component space. By bunching the medications dependent on their cure capacities to manifestations, various selections of medications can be limited to a few groups. Few valuable mobile applications exist in medicinal services region that can give helpful suggestions like, diet guidelines, different prevention's of sickness using versatile application-based recommender frameworks[28,29,30]. In[28], the authors propose a structure for building up an intelligent arrangement of virtual social insurance collaborator to help individuals, particularly for the individuals who experience the ill effects of perpetual maladies to effortlessly comprehend their well-being conditions and after that well oversee it. In another work[29], the clients pick the specialist online without adequate customized guidance using iDoctor application. The trial results demonstrated that the expectation of proposed Hybrid matrix factorization is superior to Basic Matrix Factorization. Thing-based CF, and client-based CF, and iDoctor can give extensive precise suggestion. In[30], the authors proposed a client-focused eating routine using the streamlined group calculation for fat youth with comparative connections.

In[31,32], the authors utilizes algorithm approach for information handling. In[31], the authors utilizes an imaginative time series prediction algorithm calculation to give proposals for coronary illness patients in the well-being condition. In view of examination of every victim's medicinal tests reports, the framework furnishes restorative examine reports of the patient. Similarly, in[32], an algorithm that gathers client limitations and draws the supplements, which are to be admission by clients, in light of the gathered information is proposed. Likewise, it preserves the ailment state of clients to database considering the nearness of personal ancestry acquires a few components, for example, circulatory strain, throb, and glucose level, from sensors so as to confirm the present well-being state of clients. Besides, it abstracts BMR by calculating the weight, height, and existing input data (like age, gender etc.). In[33], the authors proposed a tool-based approach at the point when the information measure is huge, and can anticipate the after effects of specific event very easily. The investigation focuses on expectation and finding of thyroid issue in ladies. By causing appropriate classification and clustering the disarranges in thyroid hormone can be avoided and reasonable medicine can be endorsed. The device mahout is incredibly convincing in separating the huge data and endorsing appropriate result. Here, the machine-based and device or tool-based techniques are used for recommender framework in any case, there is a deep learning methodology that can be used for information handling in recommender framework in human services. Over the latest couple of years, deep learning[34,35,36,37,38] has been used in recommender structures to improve the idea of suggestions. In[39], a multi-layered or deep convolutional neural systems (DCNNs) are used to utilize the rule adequately with the end goal of feature extraction and characterization of ECG crude data removed from a patient into number of classes. The classifiers quality depends upon the channel bank affirmation, the essential bottleneck in speed of a taking care of chain being given by the isolating activities. However, the efficacy of deep learning mechanisms in context to the healthcare recommendation systems still needs to be analysed through a deep learning based healthcare recommendation systems.

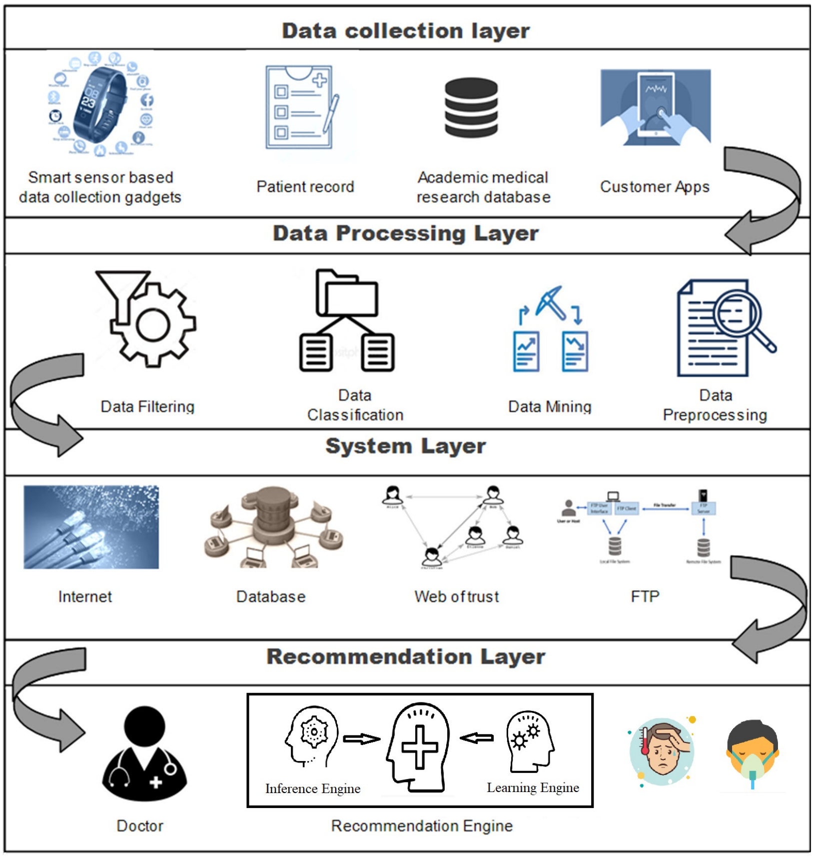

FIGURE 1 System model for the proposed recommender system.

3 | SYSTEM MODEL

The proposed system model comprises of different layers related to healthcare entities as shown in Fig. 1 . These layers are used for data collection, execution and production of output to make it usable for the doctor to give accurate decisions. In the proposed model, the data is collected from various sources that is further utilised by proposed scheme for efficient and reliable decision making and recommendations back to the user. It comprises different domains and analytical tools for filtration and separation of useful data. Further, it helps in making the decision making process easier for the doctor and the patient. The different layers of the proposed model are discussed as below.

- **Data Collection Layer**: This layer comprises of different sensor-based gazettes, wearable devices, implantable sensors, patient records, academic medical research database, customer applications and online apps. All these devices act as a data source where either the data is generated automatically (like body sensors) or the patient inputs the same (like online portals and apps). The collected data can be structured, unstructured or semi-structured and it is forwarded to the data processing layer for further course of action.

- **Data Processing Layer:** The data collected from different sources is sent to this layer for processing to extract useful information from raw data. The basic functions of this layer involve data filtering, classification, mining, pre-processing, and many more. The data is processed using various related methods and thereafter send to the recommendation engine that further decides on the recommendations related to severity and staging of the diseases.

- **System Layer:** This layer consists of all the underlying systems related or assisting the entire healthcare framework. This can include the forwarding network infrastructure connecting all the components of the model and ensuring smooth movement of the data, database technologies to store the data effectively. This layer helps in the step by step and systematic execution of different channels involved in the proposed system.

- **Recommendation Layer-** This layer includes the recommendation engine that utilizes the data provided by the concerned layer to suggest possible outcomes related to the severity and stage of the disease. In this model, we use CNN and a fuzzy inference engine to provide the recommendations to the patients based on the data collected from the source. The recommendation engine is responsible for accurate and timely decision making to provide precise recommendations.

4 | DEEP NEURO-FUZZY APPROACH FOR RISK AND SEVERITY PREDICTION

The proposed scheme is divided into three phases, 1) data processing, 2) disease classification, and 3) risk prediction and recommendation phases. Figure 2 represents the various phases of the proposed recommendation framework. These phases are described comprehensively in the subsequent subsections.

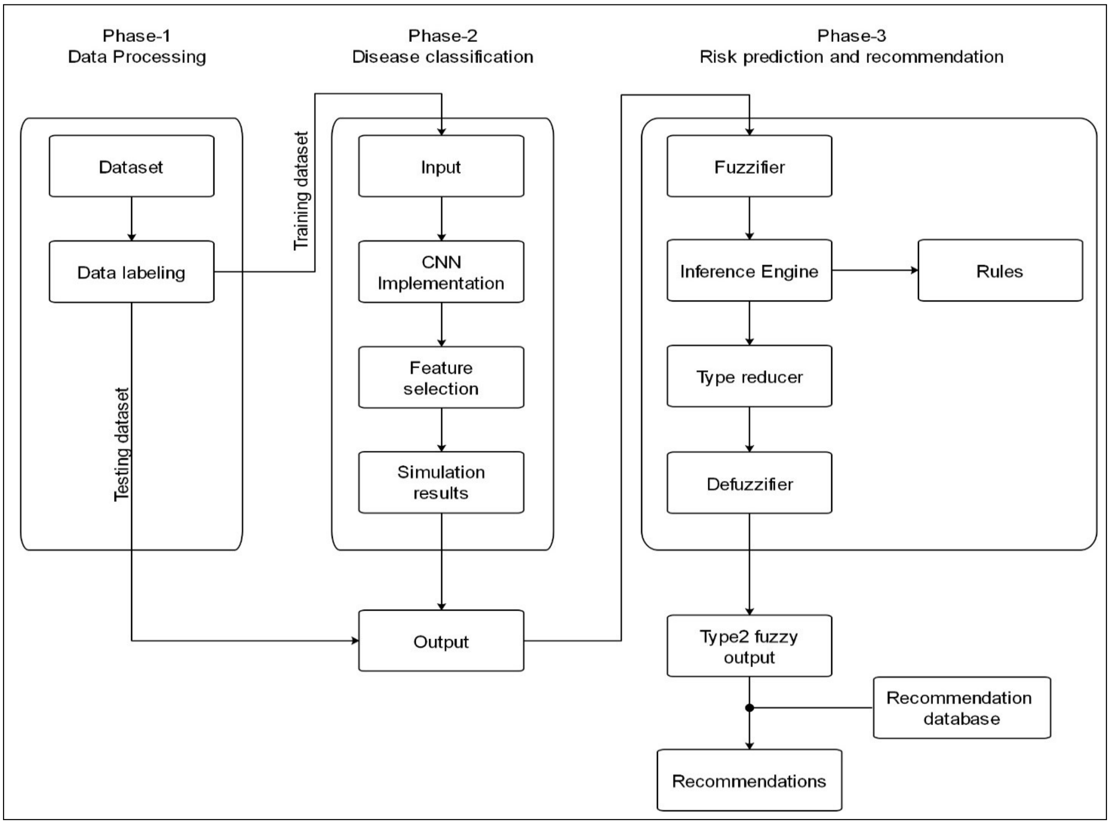

FIGURE 2 Deep Neuro-Fuzzy Approach for Risk and Severity Prediction.

4.1 | Phase I: Data Processing

In this phase, the collected data at the topmost layer is cleaned and made sure that it contains commotion free information. This information is utilized for the element choice procedure and immaterial highlight are expelled from the data, which improves the presentation of the preparation model. In the phase-I of the proposed work, after data labelling, the data is divided into two parts as described below.

- **Training Data:** The type of data is used to make the system learn on how to apply the underlying technology to produce or generate sophisticated outcomes.
- **Testing Data:** This type of data relates to the actual data that is tested using a trained model for the generation of outcomes as desired.

4.2 | Phase II: Disease Classification

The disease features are mapped to the preparation architecture model, that further arrange the mapped features for the disease forecasting. It is the process in which class labels are predicated and it detects the disease type for the patients. In the proposed system, CNN is utilized to find the class of disease for each patient. CNN framework is formed for a particular heap of layers from many specific sorts of layers. The initial step of preparing a convolutional neural system (ConvNet) is used to characterize the system engineering. Figure 3 represent the different layers of CNN. These layers are discussed as below.

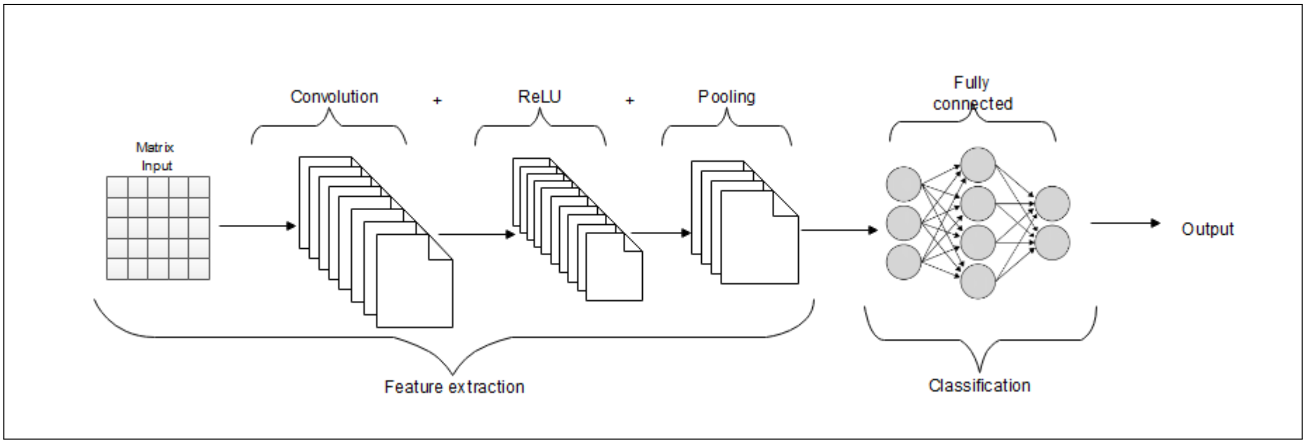

FIGURE 3 Structure of Convolutional neural Network

4.2.1 | Convolutional layer

This layer plays an activity called a "convolution", i.e., a linear operation activity that includes the multiplication of the loads or weights with the information. Let us say that considered strategy was intended for 2-D information, then the multiplication operation is applied over an array of input information and a 2-D array of the considered weights, also known as a filter or a kernel. The yield from multiplying the filter with the input information array one time is a solo value. Since the filter is applied many times over the input information array, the outcome is a 2-D array of yield values depicting the information filtering. Thus, the 2-D array yield values from this procedure are known as a "feature map". There is a formula that is used to determine the dimension of the activation or feature maps as suggested below.

$$(M_i + 2\text{Pd} — \text{F})/\ \text{S} + 1$$

where, M_i is the dimension of input file, Pd represents padding, F denotes the dimension of filter, and S represents stride.

4.2.2 | ReLU layer

This layer concerns with the contraction of the rectified linear unit (ReLU), which is used to put in the non-saturating activation function. By converting the negative quantities as zero, it successfully expels negative quantities in the activation map. Moreover, without disturbing or affecting the receptive fields of the convolution layer, it constructs the nonlinear properties of the decision function and the general system altogether. ReLU is regularly liked to different functions since it prepares the neural system a few times quicker without a significant penalty to generalization accuracy. The size of the input data, i.e., p and q share a similar size and ReLU layer doesn't affect or change the same. The ReLU, c_c m relates with the operation of truncation independently for each component in the input data as below.

$$q_{(i,j,d)} = max\left\{0, p^l_{(i,j,d)}\right\} \tag{1}$$

where, $0 \le i < H^l = H^{(l+1)}, 0 \le j < W^l = W^{(l+1)}$ and $0 \le d < D^l = D^{(l+1)}$. Based on above, it is obvious that

$$(d\,q_{(i,j,d))/(}d\,p^l_{(i,j,d)}) = [p^l_{(i,j,d)} > 0] \tag{2}$$

where, I is the indicator function, being 1 if its argument is true, and 0 otherwise. Hence, we have,

$$\left[\frac{\partial z}{\partial p}\right]_{i,j,d} = \begin{cases} \left[\frac{\partial z}{\partial q}\right]_{i,j,d} & if\, p^{l}_{i,j,d} > 0 \\ 0 & otherwise \end{cases} \tag{3}$$

where, p is taken as an alias of p^{l+1}.

4.2.3 | Pooling layer

The next layer, i.e., pooling layer is a type of non-linear down-sampling where a lot of non-linear functions are used to enforce pooling, out of which the max-pooling is one of the most commonly used function. The major goal of this layer is to reduce entities in the network (such as the spatial size of the representation, the number of parameters, memory footprint, and amount of computation) progressively, and thereafter control the overfitting problem. This layer operates over all the feature maps separately to form a new cluster of pooled feature maps of the same number. This process comprises the selection of an appropriate pooling operation (like a filter) that is then applied onto the feature maps. The size of the selected pooling operation/filter is always smaller in contrast to the size of the feature map. To be specific, the size of 22 pixels is applied with a stride of 2 pixels. Instead of learning, the pooling operation/filter is specified. Some of the most commonly used pooling functions are provided below:

- **Average Pooling:** It computes the average value of each patch on the feature map.
- **Max Pooling:** It computes the maximum value for each patch of the feature map.

4.2.4 | Fully connected layer

Lastly, after performing numerous convolutions as well as max pooling, the fully-connected layers comes into action. Its performs the highest-level reasoning in the neural network. Fig. 4 elaborates the flowchart of the disease classification algorithm.

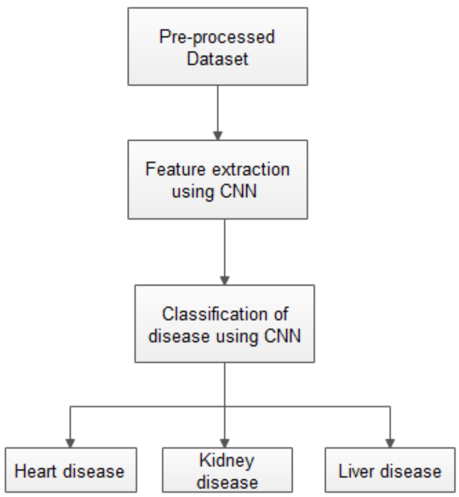

FIGURE 4 Disease classification flowchart

CNN Classification algorithms have been utilized to prepare the model to find disease classifications. The collected data is divided into two parts training and testing data and then the classification is applied on training data. As explained above CNN has multiple layers and it is defined and builds using initialization function and thereafter the parameters (like the size of CNN object, filter, padding and stride) are set as input for the convolutional layer, that returns the feature map. In pooling layer, the pooling function operates on each feature map independently and creates a new set of the same number of feature maps and reduces the size of each feature map by a factor of 2. This process continues and on a fully connected layer, the number of nodes should match the number of labels in data defined as PLabels. As a result of the CNN classification algorithm, the CNN classifier is returned which defines the different class of disease like heart, kidney and liver. To achieve the accurate prediction of disease, the results are processed with tested data. Algorithm 1 presents the above described phase of the proposed scheme.

Algorithm 1 Disease classification algotihm

Input: Data, D
Output: Type of disease

```
READ data ≥ {D}
{D}tr ≥ {D} [0:X]
{D}test ≥ {D} [X+1:N]
CNN = initcnn(CNN, [h,w])                                  ▷ Initialize CNN with size [h,w]
SET (F,P,S)                                                ▷ Define Filter, Padding, Stride
Define cnnAddConvLayer(CNN, F, S, P, sigmoid(x))
F.M= [[N+ 2p-K]/S] +1]                                     ▷ Feature map
Define Pooling(CNN, subsampling type, subsampling rate) as PLabels
SET classifier                                             ▷ CNN classifier
for (i in 0..PLabels) do
    if (i == PLabels.size) then
        Classifier = (CNN, PLabels)
    end if
end for
Type of disease = (Classifier, {D}test)
```

4.3 | Phase III: Risk Prediction and Recommendation

Type-2 fuzzy system-based risk and severity prediction scheme is used to first find the risk of disease to the patient on the basics of severity range prediction performed using fuzzy logic. Fig. 5 presents the structure of a type-2 fuzzy logic inference system, which comprises of different elements, such as, a fuzzifier, a rule control, an inference engine, a type reducer, and a defuzzifier. All these elements are described in the subsequent subsections.

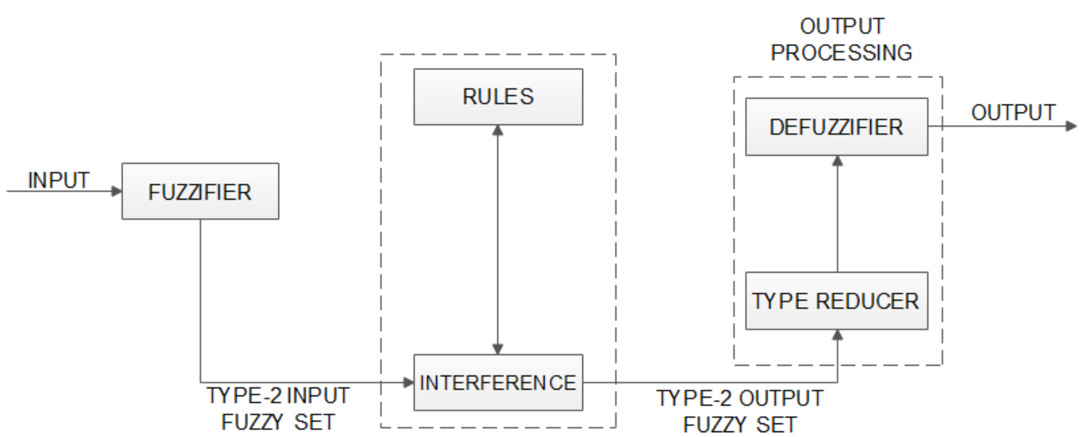

FIGURE 5 Type-2 Fuzzy

4.3.1 | Fuzzifier

The basic function of fuzzifier relates to the update or change of the set of input values (that are used as input data to a fuzzy logic system) into a cluster of fuzzy values. The fuzzifier uses Gaussian primary membership functions, that is depicted as below.

$$\mu_A(a) = exp[-\frac{1}{2}(\frac{a-m}{\sigma})^2], m \in [m1, m2] \tag{4}$$

where, m denotes mean and σ represents the means standard deviation.

4.3.2 | Rule Control

The input data to a type-2 fuzzy system $[a1 \in A1, a2 \in A2,$.......and $ap \in Ap]$ and the corresponding fuzzy output sets are $y \in Y$, R^i : $I\Gamma a_1$ is $\bar{F}$ and $a2$ is $\bar{F}$...and a_p is $\bar{F}$ then y is $\bar{G}$. Here, $\bar{F} = [\mu(a), \bar{\mu}(a)]$ denotes the j^{th} antecedent of rule i and $\bar{G}$ indicates the consequent of rule i.

4.3.3 | Inference Engine

Being a key component, the inference engine is responsible to compute a firing level that is a weight associated with each of the fired rules. The firing level is based on the input and the predecessor of the rules. It is applied on the firing levels to get the subsequent fuzzy sets. The upper and lower firing levels for the subsequent, Gi, is given as below.

$$f\left(a'\right) = \min\left\{\mu\left(a_l\right), \mu\left(a_2\right), \mu\left(a_3\right)\right\} \tag{5}$$

$$f^l\left(a'\right) = \min\left\{\mu\left(a_l\right), \mu\left(a_2\right), \mu\left(a_3\right)\right\}$$

4.3.4 | Type Reducer

The output set for each associated protocol in the type-2 fuzzy logic inference system is known as a type-2 set. This set is reduced into type-l fuzzy set $[y_r, y_s]$ to achieve computational efficiency using the centre-of-sets type-reduction technique. Here, y_r and y_s are two endpoints used to decide the interim set as depicted above. They correspond to the centroid of the type-2 interim consequent set, $\overline{G}$ of the i^{th} rule. The calculation of y_r and y_s is described as below.

$$[y_r, y_s] = \left[\frac{\underline{y_{r+I}}\ min\{\frac{\sum_{i-1}^{M} \underline{f}^i y_l^i}{\sum_{i=1}^{Rejectt1} \underline{f}^{i'}}, \sum^{Rejectw} f^t \sum_{i=1}^{\bar{Rejectt1}} \frac{iy}{\bar{f}^i}\}}{2}, \frac{\bar{y} + max\left\{\frac{\sum_{ir}^{Rejectw} f^i \bar{y}_s{}^t}{\sum_{i=1}^{Rejectt1} \bar{f}^i}, \frac{\sum_{i-r}^{M} f^i \bar{y}_s{}^t}{\sum_{i=r}^{Rejectt1} \bar{f}^i}\right\}}{2}\right]$$

$$\underline{y_r} = min\left\{\frac{\sum_{i=1}^{M} \underline{f}^i y_i{}^i}{\sum_{i=r}^{M} \underline{f}}, \frac{\sum_{i=1}^{M} \bar{f}^i y_i{}^i}{\sum_{i=r}^{M} f^i}\right\} - \left[|\frac{\sum_{i=1}^{M}(\bar{f}^i - \underline{f}^i)}{\sum_{i=1}^{M} \bar{f}^i \sum_{i=1}^{M} \underline{f}^i} * |\frac{\sum_{i=1}^{M} \underline{f}^i(y_i{}^i - y_i{}^r)\sum_{i=1}^{M} \bar{f}^i(y_i{}^M - y_r^i)}{\sum_{i=1}^{M} \underline{f}^i(v_i{}^i - v_i{}^r) + \sum_{i=1}^{M} \bar{f}^i(v_i{}^M - v_r^i)}\right]$$

$$\bar{y}_s(a) = max\left\{\frac{\sum_{i=1}^{M} \bar{f}^i y_s{}^i}{\sum_{i=1}^{M} \bar{f}^i}, \frac{\sum_{i=1}^{M} \underline{f}^i y_s{}^i}{\sum_{i=1}^{M} \underline{f}^i} + \right\} + \left[|\frac{\sum_{i=1}^{M}(\bar{f}^i - \underline{f}^i)}{\sum_{i=1}^{M} \bar{f}^i \sum_{i=1}^{M} \underline{f}^i} * |\cdots \frac{\sum_{i=1}^{M} \underline{f}^i(y_s{}^i - y_s{}^r)\sum_{i=1}^{M} \bar{f}^i(y_s{}^M - y_s^i)}{\sum_{i=1}^{M} \bar{f}^i(y_s{}^i - y_s{}^r) + \sum_{i=1}^{M} \underline{f}^i(y_s{}^M - y_s^i)}\right]$$

4.3.5 | Defuzzifier

The defuzzification function is applied over each type-diminished set to obtain a hard output from the type-2 fuzzy logic inference system. The average of the type-reduction set represents the defuzzified value and it is obtained using the below function.

$$y(a) = yr + ys/2$$

4.3.6 | Severity prediction and recommendation

After disease prediction, the scope of exposure parameters are distinguished and relying upon the range and risk factor, the severity estimations are identified. The data gathered is matched with the rule set to identify the severity level. The severity value and importance value from information base is used to process the last score value. Followed by the classification of the specific type of the disease, the results are depicted by the fuzzy system according to the rules. The results of the fuzzy input are obtained in terms of different levels which are normal, high, medium and low. As defined in Fig. 6 of risk prediction, after performing the classification on the data set, recommendations are generated for patients by collecting the outputs of analysis.

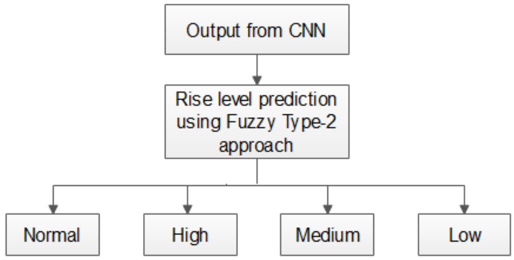

FIGURE 6 Risk prediction flowchart

A criterion is generated from the recommendation database, severity and risk level estimation for generating recommendations. The four general types of recommendations which are assigned to the patients, 1) normal exercise, 2) need to visit doctor, 3) need to get hospitalized, 4) no recommendations needed. After disease classification, the range of parameters for feature set are identified and depending on the range of severity, the risk levels are identified. For different diseases, the range of parameters in the feature set is different, like for heart disease patient the parameters p1 and p2 are cholesterol and blood pressure, respectively. This is the last phase implemented in the proposed system. Algorithm 2 presents the above-described phase.

Algorithm 2 Risk predication and recommendation algorithm

Input: Input: Data: D, Type of disease: P
Output: Outputs: Recommendation

```
def definer (Type of request)
if V == N then                                              ▷ V= Severity range
    while (S >0, S <0.5)
        //Add decrement or increment for S in loop do
        S= Match severity score
        Else
        if V == H then
            while (S >0.5, S <1)
                //Add decrement or increment for S in loop do
                S= Match severity score
                Else
                if V == VH then
                    while (S =1, S >1)
                        //Add decrement or increment for S in loop do
                        S= Match severity score
                        return S
                        {F}∈P where P∈p1,P∈p2, K∈F.V    ▷ F= feature set, K = recommendation database
                        for (P=1 to n) do
                            S=definer(@ type of request)
                            (S range 0-1)
                            if (0<S<0.5) then
                                return 1
                                if (0.5<S<1) then
                                    return 2
                                    if (1=S>1) then
                                        return 3
                                        if (S<0) then
                                            return 4
                                        end if
```

5 | EXPERIMENTAL SETUP AND DATASET

This section presents the experimental setup for the assessment of the proposed prediction and recommendation scheme. The patients are diagnosed on the basis of the data sets retrieved for three type of diseases (heart, liver, and kidney). The proposed work involves three stages to diagnose the disease, i.e., classification, prediction, and recommendation. These stages consist of different techniques implemented in the proposed scheme.

5.1 | Dataset used

The proposed work incorporates data sets with different disease, i.e., heart, liver, and kidney. Each of the disease comprises different factors, thus, no database contains the entire same factors for each type. The datasets are recovered from UCI library [1]. In the considered dataset, 1032 patients are recorded based on the health features and conditions described in Table 1 . In total, 43 attributes and three output classes are defined for each patient. The information from the dataset is utilized for training and testing purpose. The data is prepared so as to anticipate the required output class from the information of the patient. The ratio of training to testing data usage is 4:1.

TABLE 1 Health attributes of considered dataset

Common Attributes	Attributes of Heart Disease	Attributes of Liver Disease	Attributes of Kidney Disease
age	cp (chest pain type)	TB Total Bilirubin	sugar
sex	trestbps (resting blood pressure)	DB Direct Bilirubin	rbc (red blood cells)
hemo (hemoglobin)	chol (serum cholestoral in mg/dl)	Alkphos	pc (pus cell)
pcv (packed cell volume)	fbs (fasting blood sugar)	Sgpt Alamine Aminotransferase	pcc (pus cell clumps)
wc (white blood cell count)	restecg (resting ECG)	Sgot Aspartate Aminotransferase	ba (bacteria)
rc (red blood cell count)	thalach (maximum heart rate)	TP Total Protiens	bgr (blood glucose random)
htn (hypertension)	exang (exercise induced angina)	ALB Albumin	bu (blood urea)
dm (diabetes mellitus)	oldpeak (ST depression induced by exercise relative to rest)	A/G Ratio Albumin and Globulin Ratio	sc (serum creatinine)
cad (coronary artery disease)	slope (slope of the peak exercise ST segment)	sg (specific gravity)	sod (sodium)
appet (appetite)	ca (number of major vessels (0-3) colored by flourosopy)	al (albumin)	pot (potassium)

5.2 | Parameters considered for classification

[1] https://archive.ics.uci.edu

In the proposed scheme, the CNN approach is used to detect the disease type of the patient. The parameters selected for the CNN model are shown in Table 2 . CNN is responsible of classifying the disease according to the trained model. CNN classifier works according to its layered architecture, but the number of layer and their type is dependent on the data or the application where CNN is being used. The results for the classification process are obtained to reveals the health conditions of the patients according to the vital parameters available. The patient can be diagnosed with illness related to the liver or kidney or heart. After the diagnosis of the health issue in the patient, the prediction phase is implemented to determine the risk level of disease.

TABLE 2 Parameters of CNN

Sr. No	Parameter	Value
1	Optimizer Type	Stochastic gradient descent with momentum (SGDM) optimizer
2	Maximum Epochs	30
3	Initial learn rate	le-3
4	Learn rate schedule	Piece wise
5	Learn rate drop factor	0.1
6	Learn rate drop period	20

5.3 | Parameters considered for prediction and recommendation

The prediction phase includes identification of risk level of disease to the patient. Fuzzy type 2 system uses the rules to decide as described manually by the user after considering all the possible causes of the data obtained for the patient's health. For each case (i.e., for heart, liver, and kidney), the precise values required for a healthy human being are retrieved from the experts and are used to analyze the risk level. For each type of health concern, the rules are generated by taking into account the different values of parameters required to stay fit. These values are extracted from experts and are recorded for each case. The factors chosen for the considered disease are given below along with their ranges for a healthy patient and affected patient.

5.3.1 | Heart

The heart is reasonable for pumping the blood human body and there many factors that affect its working in a human body. The proposed works take into account, 1) Cholesterol and 2) Blood Pressure for this disease. The cholesterol level of the patient helps to identify the level of illness related to heart. It also presents the blood pressure level to verify the probability of the disease. Table 3 shows the different levels of cholesterol and blood pressure that affect the human body.

TABLE 3 Level of cholesterol and blood pressure to check heart disease

Cholesterol	
Range of Cholesterol (mg/dL)	**Risk of Heart Disease**
100 mg/dL - 129 mg/dL	Fit (No Disease)
130 mg/dL - 159 mg/dL	Border Line
160 mg/dL - 189 mg/dL	High
190 mg/dL and above	Very High
Blood Pressure	
Range of BP (mm Hg)	**Risk of Disease**
90/60 (low)	High
120/80 (Normal)	Fit(No Disease)
140/190 (High)	Very High

5.3.2 | Liver

The liver helps in the process of digestion and absorption of the food. The factor selected to detect the health condition related to the liver disease are, 1) Alanine Aminotransferase (ALT), and 2) Aspartate Aminotransferase (AST). ALT is also known as Serum Glutamic-Pyruvic Transaminase (SGPT) and AST is known as Serum Glutamic-Oxaloacetic Transaminase (SGOT). Normally the level of both AST and ALT is low in human blood. The normal values required for a healthy liver are recorded in Table 4 . If the tests show less or more values for ALT and AST than the values given in the table, it ensures that the patient is at the risk and is not healthy.

TABLE 4 Normal Levels of SGOT and SGPT in human body

Factors for Liver	Minimum	Maximum
Ala nine Aminotransferase (SGPT)	7 Units	56 Units
Aspartate Aminotransferase (SGOT)	10 Units	40 Units

5.3.3 | Kidney

The main function of the kidney is to extract the waste from the human body and maintain the volume of fluids required in the body. To check the illness related to kidney, the proposed work has taken into account, 1) serum and 2) Potassium levels. These factors play a vital role in keeping the kidney healthy. These values are provided to the fuzzy engine to decide the health condition of the kidney. Table 5 presents the required values to decide an effective way. The unit here taken are mmol/L i.e. micromole/litres.

TABLE 5 Level of Potassium and Serum Creatinine in Human Body

Potassium		
Range of Potassium (mmol/L)		**Risk of Disease**
3.6 - 5.2 mmol/L		Normal
5.3 - 5.5 mmol/L		High
Above 6 mmol/L		Very High (Life Threatening)
Serum Creatinine		
Gender	**Minimum Value (mmol/L**	**Maximum Value (mmol/L)**
Male	60	120
Female	50	110

5.3.4 | Output of fuzzy engine

After classification, the results are depicted by the fuzzy system according to the prescribed rules. The results of the fuzzy input are obtained in terms of different levels as explained below.

- **Normal**: This output is obtained when the data retrieved for the patient is according to the required values of the selected parameters.

- **High**: This output refers to the high-risk level for the specific disease. It suggests that the patient must get a treatment to control the risk of disease.
- **Medium**: Fuzzy gives the output as a medium when the data obtained for the patient's particular test is neither high nor less than a specific level. The patient has a medium risk of being diagnosed for the disease.
- **Low**: When the output of fuzzy is low, it shows that the patient is diagnosed with the disease which has low risk in affecting the health of the patient. It shows the patient is normal and is not prone to the disease.

6 | RESULTS AND ANALYSIS

The experimental results carried out in terms of different cases are explained above to analyse the efficacy of the proposed scheme. The results obtained for each phase are defined as below.

6.1 | Output for classification phase

From the classification phase, to check the adequacy of the proposed system, the data is used in different ratio for the training and testing purposes. Along with this, the output is obtained in terms of accuracy, specificity, sensitivity and root mean square error. The results obtained after experimental analysis for six different cases are recorded in Table 6 .

TABLE 6 Experimental analysis of classification in terms of different parameters

Sr. No.	Training	Testing	Accuracy	Specificity	Sensitivity	RMSE
1	50	80	0.946667	0.992054343	0.857142866	0.985175
2	50	60	0.956452	0.993662	0.857142866	0.855927
3	80	50	0.990329	0.998302758	0.833333313	0.702545
4	30	60	0.919355	0.987423182	0.8333	1.192065
5	80	100	0.997093	0.999538541	0.857142866	0.770265
6	30	70	0.893548	0.833333313	65535	1.266765

The obtained accuracy for the proposed scheme is shown in Fig. 7 . The obtained results seem promising while changing the proportions of training and testing datasets. The figure shows the highest accuracy at 8:5, i.e., when more data is used for training purpose than testing purpose. Although the accuracy remains 90 and above for all proportions of the testing-training combinations with a range between 89.9 to 99 percent. Similar interpretations can be seen for other evaluation parameters shown in Table 6.

6.2 | Outcomes for prediction and recommendation phase

The risk of diagnosed disease is predicted on the basis of the classification process. Fuzzy system takes the input from the classification process and determines the risk level. Total 200 patients with different identities are tested using the proposed system. The output obtained from fuzzy system is shown in the Table 7 . The table shows the combined results of prediction and other phases. The recommendation is given to the patient according to the risk level predicted by the fuzzy system. In this table, 10 different patients are taken and the output is retrieved in terms of type of disease, and level of risk for specific patient. The table represents the different levels and it relies on the type of the risk level.

- When the fuzzy output is 0, it declares the patient as a healthy patient and do not provide any recommendation.
- When the fuzzy output is 0.25, the risk level is considered as "low", the recommender system suggests working out daily to avoid the disease.

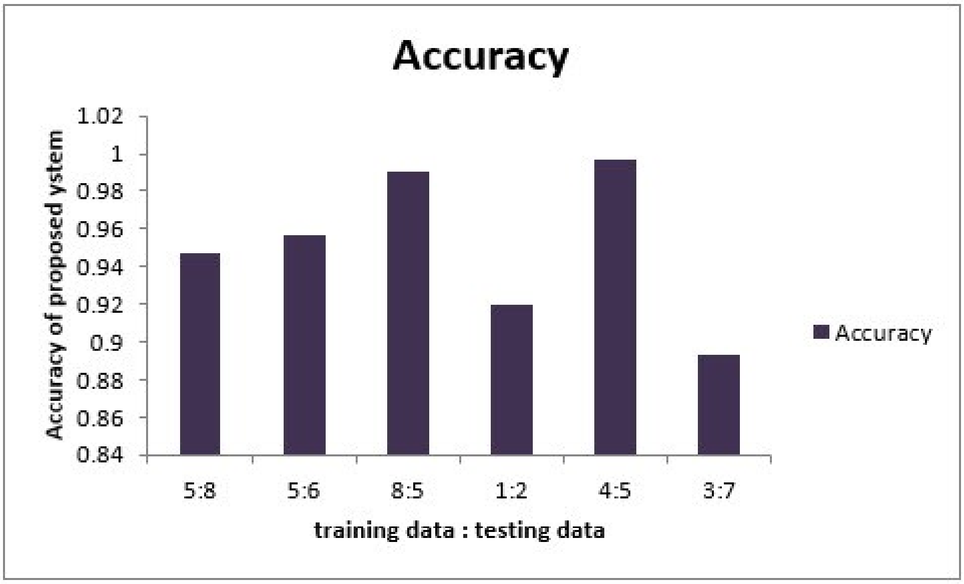

FIGURE 7 Accuracy of the proposed classification scheme

TABLE 7 Sample table for prediction

Sr. No.	Patient Id	Disease	Level	
1	92	Heart Disease	0.5	Patient need to visit doctor
2	121	Heart Disease	0.5	Patient need to visit doctor
3	165	Heart Disease	0.25	Patient need normal exercise
4	254	Liver Disease	0.5	Patient need to visit doctor
5	332	Liver Disease	1	Patient need to get hospitalized and have proper treatment
6	412	Liver Disease	0	Patient Need normal Exercise
7	500	Liver Disease	1	Patient need to get hospitalized and have proper treatment
8	545	Kidney Disease	0	Patient Need a normal exercise
9	610	Normal	0	No
10	612	Normal	0	No

- When the fuzzy output is 0.5, it is considered as medium risk level that may affect the body, thus the patients are recommended to visit the doctor.
- When the output of fuzzy is 1, it shows the high risk level in the patient, and the system suggests admitting the patient to the hospital so that the disease can be cured with the required treatment.

However, as mentioned above, the data of 200 patients is tested in the proposed system and the results attained are compared with the actual results. It is discovered that data of 9 patients out of 200 slightly varies from the actual data. Thus, the efficiency of the proposed work is accounted to 95.5 percentage which is quite suitable.

7 | CONCLUSION

[9] In this paper, we have designed a multi-level decision making framework for healthcare recommendation systems. This system identifies the different characteristics of the patients data to classify them into disease classes using convolutional neural networks. After this, a type-2 fuzzy engine is used for risk analysis and finally a recommendation algorithm has been designed to provide the recommendations to the patients based on the severity staging of the disease. For evaluation purpose, three disease were considered, i.e., heart, liver, and kidney. The results were analysed based on the accuracy, specificity, sensitivity and root

mean square error. The outcomes look very promising and the accuracy for different evaluations ranges between 90 to 99 percents. Moreover, even after variation in the testing and training data, the results retain the accuracy between the range of 90-99 percent. Even, the other performance metrics depict similar performance and variations. In the future work, the proposed scheme would be evaluated using a real test bed wherein the IoT sensors are deployed and the real-time data is collected for evaluation.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created in this study. The data used in this study are openly available in UCI Library at https://archive.ics.uci.edu.

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